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# HOW PEOPLE REFLECT ON THE USAGE OF COSMETIC VIRTUAL GOODS: A STRUCTURAL TOPIC MODELING ANALYSIS OF R/DOTA2 DISCUSSIONS

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# HOW PEOPLE REFLECT ON THE USAGE OF COSMETIC VIRTUAL GOODS: A STRUCTURAL TOPIC MODELING ANALYSIS OF R/DOTA2 DISCUSSIONS[3]

With virtual purchases being a leading source of revenue for game developers, it is still unclear how players evaluate non-functional goods and the experiences those goods grant. With the use of structural topic models, this work demonstrates the dimensions of players' experience extracted from discussions in association with price changes. This work contributes to the field by decomposing virtual goods values into experience dimensions in their relationship between extracted experience dimensions and the item's price, and by a detailed description of expectation mismatch.

Keywords: virtual goods, virtual consumption, online games, purchase, evaluation

JEL Classification: M31, D90, E21, Z13

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# Introduction

The development of the gaming industry has led to the emergence of new forms of game monetization. The situation in which the developer distributes the game for free and earns money on in-game sales of virtual goods has become popular, especially in online and social games on Facebook. The market for such games is actively developing, and by 2025 its volume is expected to reach 189 billion US dollars according to Adroit Market Research[4].

As the market for virtual goods grows, more studies of consumption in online games emerge. For the purpose of this article, we look at three perspectives on consumption: studying the psychological factors of virtual goods purchases, understanding customer experiences of virtual consumption, and dissecting virtual goods value into the components making the purchase valuable.

The current paper extends previous work, updating and specifying what dimensions of the player's experience exists in the discussions, extending the previous study (Musabirov et al. 2017), and estimating the prevalence of each dimension in the discussions, in terms of their relative importance for players.

The paper also explores the relationship between discussions of virtual items and their market value. The study shows which dimensions of player experience are positively or negatively associated with price changes, revealing what players perceive to play a role in an item's value.

In order to do that, we analyze logs of virtual goods discussions combined with data of virtual goods prices on an official game market. By doing so, we explore players' reflections on their experiences of using virtual goods and how these reflections are connected to price changes. We analyze discussions of cosmetic items on Reddit.com on subreddit r/Dota2, which is the largest English-language community hub for the game. We match discussions to the market trade data of items to find the relationship between the perception of consumption experiences and price changes of items.

This study is conducted by using Structural Topic modeling (STM), which is a quantitative text analysis technique. STM is applied to 4,766 comments about 1,088 virtual items to understand the process of cosmetic item evaluation:

- RQ 1. What dimensions of players' experience emerge from the discussions of virtual items?
- RQ 2. What is the relative prevalence of the extracted dimensions in the discussions?
- RQ 3. How are the dimensions of players' experience connected with the price changes of virtual items?

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[4] https://www.adroitmarketresearch.com/press-release/virtual-goods-market

# Background

Dota 2 is a game in the genre of Multiplayer Online Battle Arena (MOBA) that was released by Valve in 2013. Dota 2 gameplay consists of short sessions (0.5–1 hour) with two teams of five players fighting against each other in an attempt to destroy the enemies' base. Each player operates a virtual avatar called a "hero" with unique abilities. During a session, players earn levels and equipment for their heroes to become more powerful than their opponents. Earned equipment and levels do not transfer between sessions so that players are free to decide if they want to play the same hero or try another option in the next session.

Dota 2 is a free-to-play (F2P) game, which means that is is available for free but involves microtransactions with real money. In this monetization model, microtransactions are the primary source of income for the game developer. During beta-testing in July 2012, Valve launched an in-game store Dota2 Store[5], which let players purchase virtual cosmetic items that do not affect the gameplay (i.e., they do not make the avatar more powerful).

Three basic types of virtual cosmetic goods are an item, an item set, and a treasure chest. An item is an individual object that takes one inventory slot (e.g., head or hand) and changes a part of the visual model. The items united into a set usually have a common theme and color scheme. The players can combine items from different sets and obtain separate items without acquiring a whole set.

Some items have additional visual effects that change the animation of a hero's actions and magic abilities. Two characteristics of visual effects are Rarity and kinetic gems. Each item has a property called "Rarity" with eight classes: Common, Uncommon, Rare, Mythical, Legendary, Immortal, Ancient, Arcana. While common rarity describes the items with no visual effects, Arcana items can change the whole model of a hero, ability icons, and the visual effects of abilities. Another source of effects is "kinetic gems," which can be added to or extracted from the item, transferring the effect associated with them.

The treasure chests include several sets or separate items of the same Rarity. Once bought, the treasure chest gives a player one item (or set) chosen randomly and then disappears. Despite being of the same Rarity, some objects have lower chances of being given away (users refer to these chances as "drop chance"), and those items are significantly more difficult to get in comparison to the items with a normal chance. It creates additional inequality of the distribution among items and increases the scarcity of particular items.

In Dota 2, there are several common ways to acquire cosmetic items: the Dota2 Store, the Steam Community Market[6], and in-game activities. The Dota2 Store is the primary source of virtual goods for players. It includes most of the sets or the items and treasure chests that players can purchase for a fixed price. The Dota2 Store is also a source of in-game objects which reward players with items and treasure chests for accomplishing various in-game activities such as tournament betting, predictions of match outcomes, and quests.

[5] http://www.dota2.com/store

[6] https://steamcommunity.com/market/search?appid=570

The Steam Community Market is a secondary market for the players who are willing to sell items. The Market uses real money transferred into steam wallets, and though the players use real money to trade, they cannot withdraw money from Steam. In the Steam Community Market, the players set the price themselves, and the market is mostly unregulated by the developers, who do not interfere with the price formation process. However, developers take a commission for each trade deal and also make some items unavailable to trade in the market.

### Free-to-play model

The main difference of Free-to-play (F2P) games in comparison to classical models is that they are distributed to players for free, but pieces of the content can be purchased for real money, and a game usually has online or social components. According to Dredge (2013), 92% of downloaded applications on the AppStore, and 98% of downloaded applications on Google Play are F2P.

Overall, F2P is controversial in the game industry. Even though there is a generally positive opinion among practitioners about the F2P model, the ethics of F2P games is questioned because game developers tend to use dark design patterns to reinforce the sales (Alha et al. 2014).

One of the most popular F2P models is a *Pay-for-visual* model (Gyuhwan and Taiyoung 2007), which provides players with additional decorative content such as the alternative appearance of avatars or interface visual enhancement. This model is becoming more popular in the industry as it does not place players in the unfair position as the Pay-to-win model does, and it does not discourage players from staying in the game as Pay-to-pass-boring games do (Heimo et al. 2018). According to this classification, Dota 2 is a pay-for-visual game that provides players with only cosmetic goods that do not affect the gameplay.

## Related work and Theoretical Framework

### Approaches to studying virtual items consumption

For the purpose of this study, we distinguish three groups of virtual consumption studies. The first group of studies is focused on the psychological factors of virtual goods purchases (Hamari and Keronen 2016; Bleize and Antheunis 2019; Hamari and Keronen 2017). The second group of studies is led by human-computer interaction and electronic commerce research and is focused on the experiences virtual items create and the practices which make players interested in using the items (Toups et al. 2016; Musabirov et al. 2019; Musabirov et al. 2017; Bowser et al. 2015). The last group is based on an understanding of the social nature of virtual consumption (Lehdonvirta 2009; Lehdonvirta, Wilska, and Johnson 2009; Marder et al. 2019). In particular, the research is focused on the virtual goods attributes which drive players to purchase items.

Studies of the first group are usually positioned at the intersection of psychology, marketing, and game design, and tend to focus on factors which define the decision making about the purchase of goods. One of the latest literature reviews (Hamari and Keronen 2016) describes how two aspects of purchasing behavior are studied. Firstly, scholars study the factors which define purchase behavior. In this regard, habit and purchase intentions are factors that play a vital role in the purchase (Hamari and Keronen 2017; 2016). In other words, players are led either by purchase intention or habit. Unlike intentions, habits do not explain why users decide to buy virtual assets in the first place.

The intention, on the contrary, makes it possible to find out what drives people to purchase virtual goods. A meta-analysis of virtual consumption studies (Hamari and Keronen 2017) shows that such psychological factors as attitudes have the largest correlation with purchase intention (corr = 0.7 among studies). Other well-correlated factors are flow, network size, self-presentation, and subjective norms that are correlated with the purchase intention (0.4). These factors demonstrate a variety of individualistic and social reasons for players to purchase virtual goods.

It has been several years since the publication of the literature review, but the field has not changed dramatically. The only major difference observed is the growth of works related to virtual consumption in the context of mobile gaming (e.g., Balakrishnan and Griffiths 2018) and an increase of interest in online gambling games (Macey and Hamari 2019).

Another group of studies deals with the experiential side of virtual goods. The researchers in this field focus on game design and player experiences more than psychological models of decision making. For example, Toups et al. (2016) describe items from the point of view of collectible practices. They view the game as a system of rules devised by the developer. The rules define the goals and objectives of the players associated with both common and personal achievements.

The change of focus from objects to the accompanying processes is well described in a study of the consumption of vintage goods (Bowser et al. 2015). Though this study is not focused on purchasing virtual goods, it sheds light on the process behind acquiring second-hand goods. Consumers felt pleasant sensations from searching for and choosing items. Choosing the right thing is like solving a puzzle, where the final picture will be your unique appearance.

Studies of communication about virtual goods on Reddit (Musabirov et al. 2017; Musabirov et al. 2019) show that consumers use a range of logics and activities when evaluating virtual items or merchandise related to professional players. For example, the practice of collecting and combining items into a unique look was found. The players discussed the rarity and aesthetic quality of items and judged if the item corresponded to the lore and background of their hero.

The last approach is focused on a general understanding of the evaluation of virtual goods. The most common classification of types of item values is the division into emotional, social, and functional (Guo and Barnes 2011; Kim, Gupta, and Koh 2011; Lehdonvirta 2009).

Functional attributes express the ability of an item to be helpful in achieving a particular goal. The goal can be related to the accomplishment of the game quest, getting an achievement, or even the desire to look better. However, Lehdonvirta also acknowledges the presence of items lacking functional value, and those types of items, as he suggests, have hedonic or social attributes (Lehdonvirta 2009).

Lehdonvirta defines hedonic attributes as the properties which evoke visual or aesthetic pleasure and pleasant emotions in their owners. The most important aspects of a hedonic attribute are the appearance of a virtual item and the visual effects it creates when used. According to Lehdonvirta (2009, p. 102), hedonic value is a mix of pleasure and aesthetics expressed in visual and sound representation.

Another dimension of item evaluation is based on the ability of virtual goods to highlight the owner's status or of belonging to a specific group. The value which expresses the social position and self-identity of the owner is called the social value and has its roots in the early sociological theory of consumption proposed by Veblen (2017). Lehdonvirta applies his theory of conspicuous consumption to online games in an attempt to describe the social value of virtual non-functional goods. It is worth noting that each item has a mix of functional, hedonic, and social values, and why players want to purchase it depends on the proportion of these values. In the case of goods with no functional value, the good can be called non-functional, cosmetic, or decorative.

Recent work on this topic (Marder et al. 2019) supports the findings of Lehdonvirta's work and extends the analysis of emotional and social value in virtual consumption. Analyzing interviews of League of Legends players, the authors extracted nine key themes and found that emotional (hedonic) motivation has five aspects important for players: novelty, aesthetics, reciprocity, self-gratification, and character dedication. Social motivation consists of four components: gifting, social distinction, showing reciprocity, visual authority.

## Values as singularities of meaning

The virtual goods analyzed by Lehdonvirta are a clear example of what Karpik calls a "singularity of meaning" (Karpik and Scott 2010; Healy et al. 2011). According to his "economics of singularities," the evaluation of items with no visible utility (Karpik analyzes aesthetic goods) is a complex social process. While functional goods have a visible scale of quality, aesthetical goods have no attribute which would let customers compare two objects varying dramatically in price. Aesthetical goods are a mix of different social and symbolic aspects that together create a "singularity of meaning." While not necessarily sharing all of the details of Karpik's approach, a lot of works on valuation studies resonate in making attempts to analyze different segments of the cultural market, e.g., art (Velthuis 2007) and fashion modeling (Mears 2011), focusing on the multidimensionality of quality and status entanglement, and take a qualitative interpretive approach.

Nevertheless, there have been attempts to reveal the dimensions of evaluation of non-functional goods and to analyze their relationship with price. Rengers and Velthuis (2002) look at contemporary art pricing in the Netherlands, focusing on galleries, and taking the art, the artist and gallery parameters as price determinants. In a study of the French wine market, Beckert et al. (2016) described wine price formation mechanisms, and as Lehdonvirta did in his study of virtual items, Beckert et al. deconstructed wine into several aspects that are believed to play a role in price formation: wine age, year and place of origin, etc. Using a hedonic regression models approach, researchers revealed the relationship between those aspects and the price of wine.

Though researchers analyzed the relationships between wine characteristics using regressions, in a real-life setting, it is very difficult for customers to make calculations on the value of the goods or services they purchase (Karpik and Scott 2010). Nevertheless, they make a judgment about goods and which object to choose. Karpik suggests that people use judgment devices which help them to choose the right option and describes five types of judgment devices: *rankings*, *personal* and *not personal social networks, brands*, *ciceronis* (experts) and *guides*, and *marketing* (ibid.).

Kornberger et al. (2015) highlight that customers not only use a particular judgment device to make a decision but those devices can be used simultaneously in their interactions. Information about wine can be a judgment device that helps the customers to evaluate the wine.

## Theoretical framework and Research Questions

These approaches to studying virtual consumption cover the same process as virtual goods purchases, but they do it from three different perspectives. While marketing and psychological research are focused on the psychological prerequisites of virtual purchases, sociological and human-computer interaction (HCI) research sheds light on what makes virtual items attractive to players. In the sociological approach to this question, researchers investigate the processes of non-functional goods evaluation in general. This research mostly provides the field with models that use hedonic regressions and theories which explain how the market for non-functional goods works (Aspers and Beckert 2011; Beckert, Rössel, and Schenk 2016; Karpik and Scott 2010). HCI research focuses on what experiences virtual consumption provides the players with. In this case, the motivations to purchase items are very contextual as games have sets of constraints that differ among games and even real life (Toups et al. 2016; Bowser et al. 2015). The players can have experiences that are entangled in the design of games, which is a focus of HCI studies: to uncover the relationship between those experiences and design elements.

This work is based on a combination of sociological and HCI perspectives. It investigates the relationship between the experiences virtual items grant to players and item prices. In the same manner as previous studies (Bowser et al. 2015; Livingston et al. 2014; Toups et al. 2016), this work uncovers the usage and evaluation of items and players' reflections on their experiences of virtual cosmetic goods. It also describes the mechanisms of price formation which have a social nature as they are based mostly on a social and symbolic interpretation of what is good (Lehdonvirta 2009; Lehdonvirta, Wilska, and Johnson 2009; Beckert, Rössel, and Schenk 2016; Beckert and Rössel 2013) and what is not. Moreover, as a previous study has shown, the important role of judgment devices in the evaluation of virtual goods (Musabirov et al. 2017), we extend the discussion in this direction by taking price into consideration, answering the following research questions:

**RQ 1. What dimensions of players' experience emerge from the discussions of virtual items?**

**RQ 2. What is the relative prevalence of the extracted dimensions in the discussions?**

**RQ 3. How are the dimensions of players' experience connected with the price changes of virtual items?**

# Methodology, data, and methods

## Methodology

This study uses the mixed-methods approach known as Netnography (Kozinets 2015), which was invented to fill the gaps in traditional methods which became apparent in the studies of virtual communities.

Digital communication provides researchers with plenty of data that is already stored in the form of action logs, forum posts, messages in a chat, the information in users' profiles, etc. The new challenge here is not the shortage of data but its overwhelming amount. It becomes a problem to decide which texts are worth analysis and which texts describe the community the best.

Netnography is an approach that helps to overcome those problems. The focus of this approach is to use a wide range of methods, including computational, to support qualitative analysis. A quantitative study shows the most important patterns in the communication of the target community, highlights the most important texts describing the community and helps to interpret the revealed patterns.

To uncover the dimensions of the experience of players' communication, a topic model was estimated. Topic modeling (Steyvers and Griffiths 2007) is a machine learning-based method of quantitative textual analysis that creates clusters (called 'topics') of words often co-occurring in the same texts. Topic modeling algorithms treat texts as 'bag-of-words' and ignore word positions, their lexical meaning and punctuation, and only count co-occurring words and their frequencies. Using information about word co-occurrence, the topic model defines the groups of words that tend to occur more often than others.

A topic model produces the probability of the distribution of words in each topic and the probability distribution of topics in text documents. Each unique word is present with some probability, and each topic can be characterized by several highly probable words while probabilities of other words are close to zero. In the same manner, each text is the probability distribution of topics and can be characterized by a couple of the most probable topics, while probabilities of other topics are close to zero.

Topic modeling was chosen primarily because this method lets a researcher handle large textual data by clustering many disconnected texts into topics. Manual techniques such as thematic analysis are not suitable for large text corpora analysis, and Paul Dimaggio suggests three reasons for that (DiMaggio, Nag, and Blei 2013). First of all, manual analysis of a large body of texts is time-consuming and impractical. Second, in more complex analytical tasks, it is harder "to achieve acceptable levels of intercoder reliability" (DiMaggio, Nag, and Blei 2013; p. 577) as they demand more intersubjectivity. Lastly, a researcher usually presumes beforehand what is worth finding, which makes exploratory part of the research flawed. Topic modeling makes the analysis of large corpora less expensive, allows the reproduction of a study, and, being an exploratory method, can provide a researcher with a new scheme of themes.

Topic modeling has became a popular tool for studying large bodies of texts in virtual studies and social sciences. Some of the first researchers who applied topic models in the context of social science were DiMaggio, Nag, and Blei (2013), who studied texts of political news using topic modeling algorithm Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003). Using LDA, DiMaggio coded text documents and interpreted how media covered news related to art. DiMaggio interpreted topics as frames, which are "semantic contexts that prime [...] interpretations of the phenomenon in a reader" (DiMaggio, Nag, and Blei 2013, p. 578).

However, the topics can be treated in a more specific way than frames of interpretation. For example, Guo, Barnes, and Jia (2017) analyzed reviews on TripAdvisor and described topics as the dimensions of guest experiences in the hotels. By conducting LDA, the authors revealed 30 dimensions of guest experiences with 9 dimensions that had not been covered before. The authors analyzed the relative importance of experience dimensions in their connection to demographic information of guests, and hotel classification.

This work is based on Structural Topic modeling (STM) (Roberts, Stewart, and Tingley 2018; Roberts et al. 2013). STM creates clusters of words taking into account document metadata, allowing the estimation of connections between the topics and metadata covariates.

Recently STM has been used in social sciences and research related to experiences (Lynam 2016; Tvinnereim et al. 2017; Grajzl and Irby 2018; Chow et al. 2017). For example, Grajzl and Irby (2018) extracted themes of experiences for students studying abroad with the help of STM, and the choice of method was motivated by using metadata that makes topic modeling more precise. Researchers found themes relating to the context of the study (e.g., duration and location) as different dimensions of experiences such as immersion in a new culture, history & art, and personal growth. Moreover, the authors analyzed how students' demographic characteristics such as gender, age, and academic performance are related to extracted themes. For example, while males shared more reflection on immersion in a new culture and relating to people, females tended to share more about food and social habits.

## Data

**Item dataset.** The item dataset consists of 1,088 unique items, and dataset was constructed in accordance to several conditions: 1) items represent each rarity available in the game (see Table 1); 2) items have diverse release years; and 3) items are old enough to have discussions (new items released to the market are usually banned from trading for a particular period (see Table 2)).

**Table 1. Distribution of rarities, %**

| Common | Uncommon | Rare | Mythical | Legendary | Immortal | Ancient | Arcana |
|---|---|---|---|---|---|---|---|
| 21,3 | 20,7 | 31,5 | 13,4 | 1,3 | 10,2 | 1 | 0,6 |

**Table 2. Distribution of release years, %**

| 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|
| 13,6 | 36,7 | 31,9 | 11,9 | 5,9 |

**Text corpus.** The Reddit API was used to obtain the list of threads that mention an item from the dataset. For each item, the 100 most commented threads were gathered. Since several items were mentioned in the same thread, some URLs appeared several times. After the removal of the duplicated URLs, 2,213 unique URLs were left.

The next step was to collect the comments in each thread. The package RedditExtractor (Rivera 2019) for the statistical language R provides such a tool. The package collects up to the 500 most upvoted comments in the thread.

Each comment was labeled, showing whether it includes an item name. All comments that mention item names and replies to those comments remained in the dataset. This step allows the analysis of the discussions directly related to particular items. In total, 4,766 comments (out of 103,504 comments) include the name of at least one item. Analyzing only these comments reveal what players think about particular cosmetic items. The previous study, in comparison, (Musabirov et al. 2017) included all the comments of the thread, which helped to describe the Dota 2 trade market ecosystem in general but did not focus on aspects of only cosmetic items.

**Market price dataset.** Information about the price dynamics of the items was gathered from steamcommunity.com web API. One query collects the price dynamics data on the specific item and gives back a list of dates for a particular item with a number of sold items and the average price of sold items for each date. In total, 1,089 API queries were made, and data on 999 items were gathered as some items were absent, and API could not process the given queries.

Price per day was taken in order to detect how discussions related to price change. In this sense, it was necessary to transform data as the price in absolute numbers did not represent the price change, and the interpretation of the given variable could be wrong.

For that purpose, price change in comparison to the previous day was calculated. For each item, the order of days was defined, and then price change was found by subtracting the price on day *N* from the price on day *N-1*. More than 90% of days showed a price change. These values were categorized as Price Increases or Price Decreases. As a result, the final variable on price consisted of three categories: "Price Increase," "No Change," "Price Decrease."

**Table 3. Example of the observation in the final dataset**

| Date | Item name | Text (truncated) | Price change category |
|---|---|---|---|
| yy-dd-mm | shard of the rift | Shard of the Rift the Void weapon and the courier are the only decent ones were in … | Price Increase |

## Method

Before conducting the topic modeling, it was necessary to prepare the model by deciding which covariates would be included in the model, and by defining the optimal number of topics in the model.

The first step was to define covariates, and STM uses regression model formulas for that purpose. The regression formula was *prevalence =~ Price change category,* meaning that only the variable of price change was involved in topic modeling.

The second step was to define the optimal number of topics. In order to choose the optimal number of topics, several models with a varying number of topics (between 10 and 45 with a 5 topic step) were calculated, and model diagnostics were conducted.

According to guidelines (Silge 2018; Grajzl and Irby 2018), it is necessary to find a trade-off between high *exclusivity*, high *semantic coherence*, high *held out* probability and low *residuals* value. 35 topics were chosen because held out, and semantic coherence were not the lowest; exclusivity was almost the highest and residuals were the lowest.

The topic model identified 35 topics with different sets of the most associated words for each topic. Since the identification of topics is based on an unsupervised machine learning algorithm, the extracted topics are not affected by the biases of the researcher. However, the interpretation of topics based on the most probable words is a reflection of researcher subjective evaluation. To reduce the effect of subjectivity, we used two kinds of scores for a word association with topics and the most associated texts for each topic.

For each topic, two lists of words were presented. First, there were 7 words with the highest probability in the topic, which is based on the topic word frequency. However, in this case, the most frequent words in the whole text dataset would appear more often. For that purpose, there are also 7 words with a high FREX (FRequency and EXclusivity) score, which combines a word's probability and its exclusivity for a particular topic. In this way, FREX finds words both frequent and specific for particular topics, which makes the interpretation of the topic more precise than it would be by analyzing only Bayesian probability.

To answer **RQ 1** (What dimensions of players' experience emerge from the discussions of virtual items?), topics were interpreted based on the most probable words and example messages. Table 4 shows an example of the information necessary to interpret the topic. Based on the most probable words *look, set, like, awesome, cool,* it could be concluded that topic unites the words that express evaluation of appearance and example text supported this interpretation. After topics were interpreted, the distribution of their proportions in text corpus was calculated, answering **RQ 2** (What is the relative prevalence of the extracted dimensions in the discussions?).

**Table 4. Example of topic**

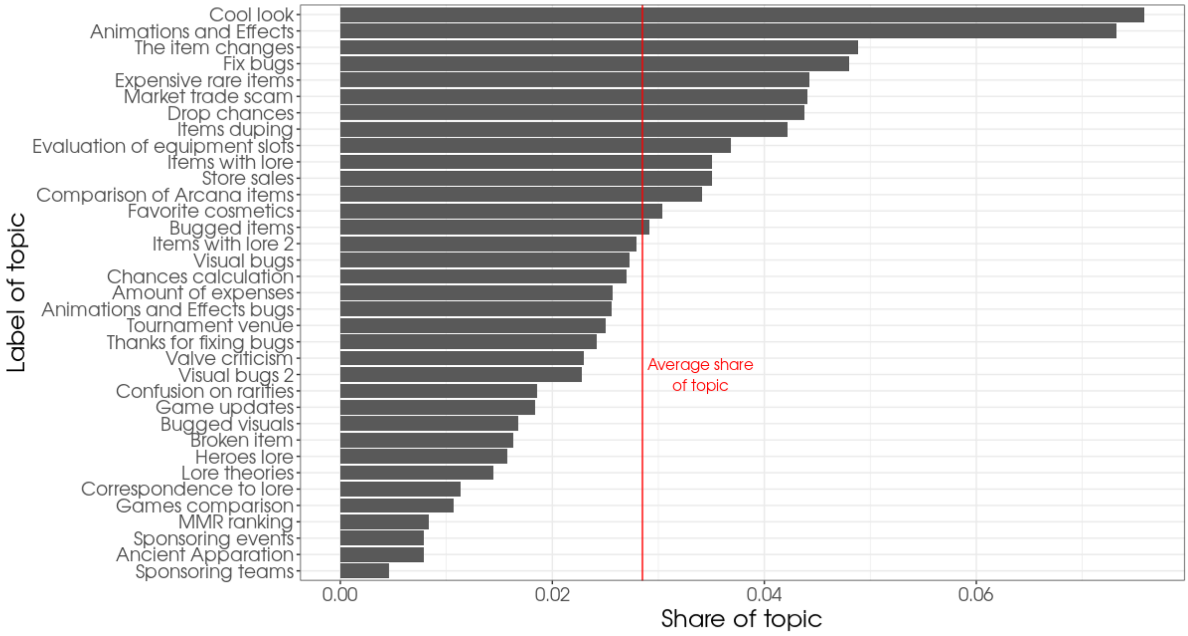
| | |
|---|---|
| Topic ID 10 | **Highest prob.:** look, set, like, realli, one, pretti, good |
| | **FREX:** look, pretti, awesom, cool, good, gold, shadow |
| I mean some of the gold ones looked alright. Like the Gold Lina dress was nice, but moreso for the spell effect, the gold riki blades from a while back look good. Golden Gravelmaw is ok, since it looks like a gold ingot for a hero of the earth. Gold Fortune's Tout was fine since those cats can often be golden to signify wealth or some shit. Gold Shadow Demon and AM from the trove look decent too. | |

In order to answer **RQ 3** (How dimensions of players' experience are connected with the price change of virtual items?), the effects of covariate "Price change category" were calculated for each topic. The STM calculated regression estimates for each topic, so there were 35 models, and each model included coefficients showing the strength of the relationship between the topic and each unique category: Price increase, No change, Price decrease. The primary interest of the study was how discussions are related to the price change; that is why the coefficients for "No change" were withdrawn from the analysis. In this study we explored how patterns of price changes connected to different evaluation mechanisms, imprinted in the discussions, thus the STM effect estimation only highlights interesting patterns, requiring additional study, which take into account the control variables and use precise measures.

STM model was built with the help of R language package stm (Roberts, Stewart, and Tingley 2018).

## Analysis and Results

**Figure 1. Distribution of topics in the text corpus**




### RQ 1-2 What dimensions of player experience emerge from the discussions of virtual items? What is the relative prevalence of the extracted dimensions in the discussions?

During the analysis, 35 topics were extracted and labeled. The topics reflect different dimensions of experiences, and those dimensions have different importance for players as their expected proportion varies between 0.5% and 7.5% of discussions. The most prevalent topics (**Cool look**, **Animations and effects**, **The item changes**, **Fix bugs**, **Expensive rare items, Market scam, Drop chances, Copying the items, Evaluation of items slots, Items with lore, Store sales, Comparison of Arcana items**, **Favorite cosmetics, Bugged Items**, **Chances calculation)** are presented in the following section as topics that take most of the discussions (see fig. 1). The topics **Confusion on rarities** and **Bugs to be fixed** do not take a large share in discussions, but they are important for further analysis and will be described as well.

This section describes the topics using examples taken from the Reddit.com comments (highlighted with *italic font*). The analysis showed three groups of dimensions that can be connected to three theoretical concepts: hedonic value, social value, expectation mismatch. Topics **Cool look, Animations, and effects, Evaluation of items slots, Items with lore, Favorite cosmetics** reveal the hedonic value (Lehdonvirta 2009) of items as they appeal to the aesthetic quality or emotional reaction of the players. Most of the topics are related to aesthetic quality, but there are also topics related to **Items with lore** (*"Here is a list of the specific items that alter the icons"*, Dockirby), which triggers a positive emotional response (Lehdonvirta 2009). Moreover, there are two types of aesthetic judgment: players either judge whole appearance of item using **Cool look** (*"Like the Gold Lina dress was nice"*, MaltMix) and **Favorite Cosmetics** *("Death Prophet's skirt is probably my favorite"*, [user deleted])) or discuss particular mechanics of making the item beautiful and combinations of dress elements that make cool look (**Animations and effects** (*"This gem was originally used to grant custom animations to [item name]*", EldRefr) and **Evaluation of items slots** (*"Jugg [hero] relic sword, Ii like 100p jug which bobs when he runs"*, [user deleted])).

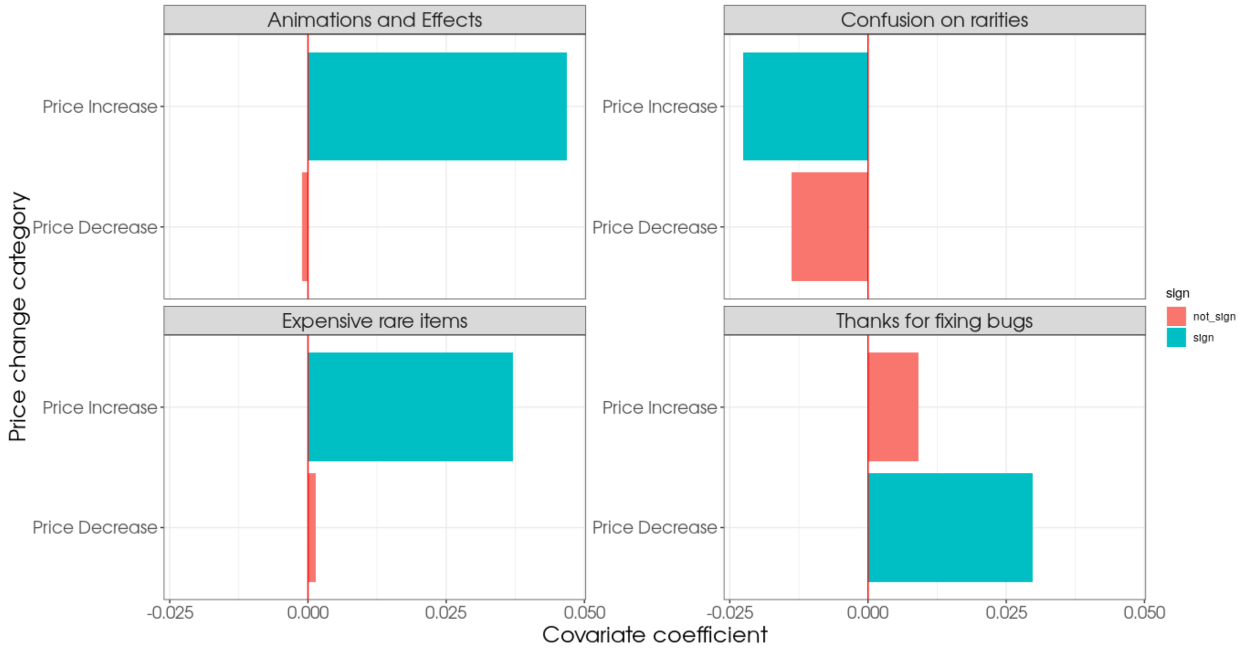
Topics **Expensive rare items** (*"Worth Upwards of $1k, roughly 50 Golden Roshans and 100 Platinum Roshans in circulation"* , Dockirby) and **Drop chances** (*"Probability of getting Item A, Item B, Item C in this particular order is: (1/10)^10 your system assumes that the chosen items are no longer in the mix"*, [user deleted]) express the social value (Lehdonvirta 2009) of items because they reflect discussions of item scarcity and its relation to item value. In this context, people discuss two things in particular: how scarce items make owners more visible in the community and how the system of getting the items works.

Topics **Fix the bugs, Market scam, Copying the items, Comparison of Arcana items, Confusion on rarities, Bugs to be fixed** reflect discussions of expectation mismatch (Musabirov et al. 2017) when the players do not get what they expected. The players can express their confusion about the items' perceived value and the price which is reflected in topics **Comparison of Arcana items** (*"Legion Commander and PA both completely remake the model [...] But look at Crystal Maiden, whose arcana is a cape"*, anarchy753) and **Confusion on rarities** (*"Not even immortals [rarity]. There are legendaries [lower rarity] that do more than immortal things"*, JaakxcyqobbqeLayque) or about failed game design that breaks trade by allowing **Market scam** (*"The same seller is listing two BladeBiters for the same price, but one doesn't have the Kinetic gem, while the other has"*, almirantecarvalho) and **Copying the items** (*"I would be mad if my Dendi signature went from 150 to 2$ overnight because of a dupe abuse"*, Saelkhas). Finally, players complain about visual bugs and try to explain why those emerge which is reflected in topics **Fix the bugs** (*"using Tentacular Timelord head without Viridus Claw makes tentacles clip with default model's chest"*, _thoax_) and **Bugs to be fixed** (*"The Terrorblade arcana still has a bug"*, *xCesme*).

**Figure 2. Example of item's price fall after duping incident**

## RQ 3. How are dimensions of players' experience connected with the price change of virtual items?

**Figure 3. Regression coefficients of topics with significant coefficients**




As a result of the STM effect estimation model (see fig. 3), four topics had a statistically significant relationship with the price dynamics category: **Animations and Effects, Bugs to be fixed, Expensive rare items, Confusion on rarities.** Though the presented effects are not larger than 0.07, they describe the change of topic proportion in texts, which is, on average, 0.0285. Despite the small number, these effects can express a rapid change of topic proportion in comparison to its proportion in the whole corpus.

The topic **Animations and Effects** has a strong positive relationship with price increases (coef = 0.047, p.value = 0.002). Based on this coefficient, we can assume that the items creating discussion of animation and effects, and thus providing hedonic value to customers, are more likely to experience a price increase. Another topic that is positively associated with a price increase is **Expensive rare items** (coef = 0.037, p.value = 0.002). Like in the previous case, the discussions on this topic are connected to price increases.

The topic **Confusion on rarities** has a strong negative relationship with price increases (coef = -0.022, p.value = 0.002). It shows that the items discussed in the context of confusion related to their rarity are less probable to experience price increases.

The only topic that has a positive relationship with price decrease is the topic **Bugs to be fixed** (coef 0.032, p.value = 0.001), which makes this topic twice as probable in texts related to price decreases. The topic shows gratitude is accompanied by complaints about unsolved bugs, and probably complaints are prevalent in the discussions on this topic. As a result, a higher proportion of the topic in the discussion of the item can reflect the higher number of people who suffered the bug, or price decreases could evoke discussions on bugs as a possible reason for the price drop.

# Discussion

To conclude, to find alternative mechanisms of price formation,  we extracted topics of discussions were explored in connection with the price change of items in comparison to the previous discussion of an item. In summary, topics reflecting hedonic (**Animations and effects)** and social value (**Expensive rare items)** are positively related to a price increase. It means that if the price of an item has increased in comparison to the previous discussion, the proportion of those topics is higher. Expectation mismatch has either a negative relationship with a price increase (**Confusion on rarities**) or positive relationship with price decrease (**Bugs to be fixed**).

Based on the analysis of Reddit.com discussions of virtual goods in their connection with price dynamics, this study brings new insights into players' experiences connected with the evaluation of virtual goods, extending previous studies in this area.

This focus of discussions on expensive items is reflected in the results of topic modeling which captures a particular discourse of discussing these goods (e.g., **Expensive rare items** and **Store sales**) and is connected with the status dimension of social value or emotional dimension of hedonic value (Lehdonvirta 2009; Marder et al. 2019).

The topic model reveals the evaluation of aesthetic value on several levels and describes the experiences of different kinds. Topics **Cool look** and **Favorite cosmetics** describe the general evaluation of the items where players judge what they find cool (Raptis, Kjeldskov, and Skov 2013) and what they do not like. The topics **Animations and effects** and **Evaluation of item slots** are focused mostly on a more specific kind of evaluation that is connected to a specific set of experiences. First of all, the visual effects have bugs that can ruin the whole experience even though the item's appearance cannot be broken. The topic **Animations and effects** is connected with positive price changes, which demonstrates that visual effects play a major role in the experience of players.

The vast prevalence of such topics supports the previous theoretical and empirical findings (Lehdonvirta 2009; Marder et al. 2019), who found that visual representation plays an important role in a player's decision to purchase non-functional items. Not only does the analysis conducted in this work demonstrate that aesthetic value plays a vital role in the evaluation of non-functional items (the range and number of topics associated with aesthetics), but also it shows how the discussion of visual effects reflects increases in the value of the assets. The analysis also shows that aesthetic value can be decomposed into different dimensions as players describe different experiences when talking about **Cool appearance** (Raptis, Kjeldskov, and Skov 2013) and **Animations and effects**.

Another dimension of hedonic value occurring in the discussions is the lore of items (topics **Items with lore),** which was suggested to be an important part of the emotional value because it includes "related background fiction or narrative presented to the user" (Lehdonvirta 2009, p. 106). Though lore is not as important as aesthetic value because the share of topic related to **lore** is much smaller (2.7–3.5%) than shares of topics related to visual effects (7.5% for **Cool look** and 7.5% for visual **Effects and animations**), it is surprising to see the presence of this dimension in Dota 2, a game with no story or thoroughly described universe. Probably a game without a rich story does not appreciate the lore element. On the contrary, the shortage of lore makes it a tool of judgment about item quality. However, further research is needed as the relation between lore and item price remains unclear.

The presence of such topics as **Expensive rare items, Drop chances, Chances calculation** reflect the interaction between an item's availability and its price. This interaction is what defines social value because scarce items have more social value as they are better at highlighting the status of players. However, these topics focus on different aspects of this experience. For example, the topic **Expensive rare items** reveals the status dimension of consumption as it consists of discussions of expensive items that are valuable due to their scarcity, and its presence has a strong positive relationship with the price increase (coef = 0.03, p.value = 0.0024). The topics **Drop chances** and **Chances calculation** are focused on mechanisms of artificial scarcity that are being decomposed by players during discussions.

The theme of the status dimension is supported by studies that identified scarcity as a primary factor of price formation (Yamamoto and McArthur 2015; Lehdonvirta 2009; Marder et al. 2019). Scarcity, in this sense, is discussed mostly as a tool to highlight the status of the owner (Lehdonvirta 2009; Marder et al. 2019).

The analysis **Expensive rare items** revealed the discussions of expensive items as a replacement for currency in trade. According to the text, expensive items are a great currency due to their limited availability and stable price. Though the usage of assets as money in barter-like trade has been mentioned in previous studies on virtual consumption (Yamamoto and McArthur 2015; Lehdonvirta, Wilska, and Johnson 2009), there is a difference which makes this example stand out. In previous studies, item-candidates for the role of ad hoc currency were widespread items that were so cheap and large in number that their value was stable regardless of game updates and other factors. For example, Yamamoto and McArthur (2015) described keys in "Counter-Strike: Global Offensive", which opened cases with virtual items as a currency that became a unified currency in unofficial trade platforms. Lehdonvirta, Wilska, and Johnson (2009) explained that players "denominated prices in plastic chairs" (p. 1072) because the game itself did not provide the players with a currency for trading.

In contrast, in Dota 2, the expensive items are treated as currency substitutes. This can be interpreted as a sign that the Steam Community Market is not a place for "premium" trading with unique items. Such trade deals possibly get done on different platforms: the famous case of EF Pink War Dog being sold for $38,000[7] was done in an auction on special subreddit r/Dota2Trade[8], taking 2 minutes for the original owner to find a buyer.

In this way, the Steam Community Market can be an inappropriate place to trade expensive items due to the service charges taken from each transaction and the impossibility to withdraw money from Steam. In this situation, the players set barter-like trade where expensive items become a unified currency for serious traders.

Topics **Market scam** and **Copying the items** reflect the mismatch between players' evaluation of items and their market price, which is perceived as an unfair and frustrating

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7 https://www.forbes.com/sites/danielnyegriffiths/2013/11/14/dota-2-three-spirits-update-38000-dollar-loot-auction/#4ccbe6c2a5c7

8 https://www.reddit.com/r/Dota2Trade/comments/1q0kxp/auction_ef_pink_war_dog_191_78_123_with_bo/

experience. Besides those topics, there are several groups of dimensions related to expectation mismatches. In particular, the analysis showed the presence of bugs and the inconsistency of rules in the system of cosmetic items.

Topics **Fix bugs** (4.7% of discussions)**, Bugs to be fixed** (2.4% of discussions)**,** and **bugged items** (2.9% of discussions) reveal the discussions of visual bugs which players face using cosmetic items. Having a real product broken makes users feel frustration; bugs have the same effect on players in the virtual world.

The difference is that real-life trade has legal regulations that protect customers in the case of broken products. In Dota 2, it is difficult to get compensated for a bugged item. As a result, players tend to value bugged items lower. This conclusion is supported by topic **Bugs to be fixed,** which includes both gratitude and new complaints and which is positively associated with price decrease (0.029, p.value = 0.0017).

Having bugs can be an example of expectation mismatch (Musabirov et al. 2017) when the real value of an asset does not comply with the expected one.

Reddit discussions provide us with another example of expectation mismatch based on the inconsistency of rules introduced by the developer. Such topics as **Comparison of Arcana items** and **Confusion on rarities** reveal the attempts of players to understand what rarity actually represents.

The inconsistency of rarity properties makes the players figure out the rules collectively in the discussion and appealing to wiki-like websites[9]. They argue for how good an item should be to have a particular rarity, what visual effects it must have, and what bugs a player expects to get when mixing arcanas with other items. As a result, discussions of rarity inconsistency and **Confusion on rarities** are negatively associated with price increase (coef = 0.022, p.value = 0.0028).

The discussions also contain references to what can be called judgment devices (Karpik and Scott 2010), or evaluation devices, used by players in purchasing items. Firstly, the topic **Confusion on rarities** demonstrates that rarity must give players some understanding of an item's value; however, as seen in the discussions, sometimes it does not work this way. Moreover, not only does it not help players decide on the item's value, but it can also contradict players’ opinions about what items are more valuable than others. This example clearly shows those judgment devices designed to help players can fail in their purpose.

Secondly, the analysis revealed the presence of lists created by players. The themes of lists are related to various aspects of the game: lists of items with bugs, lists of items with higher lore value, lists of the rarest items (and calculations of chances). Belonging to players lists itself can be a judgment device as they demonstrate players whether the items are ‘cool.’

[9] https://dota2.gamepedia.com/Rarity

# Conclusion

This paper presents the results of the study of the consumption experiences of players in Dota 2. The analysis shows particular aspects and mechanisms of two previously considered sources of value, namely hedonic and social value, and shows the mechanism of value degradation via expectancy mismatch.

A general evaluation of appearance, visual effects, and lore can be treated as aspects of hedonic value; status, and chance, in combination with the practice of barter-like trade using expensive items, are related to the social mechanisms of value construction. Inconsistency in rules, item bugs, and market system breaches constitute expectancy mismatch, decreasing the value of items: a mechanism that was only scarcely covered in previous research. Our design, which connects text data with a binarized measure of price change, is intended as exploratory, highlighting promising patterns, and requires subsequent confirmatory studies to confirm and analyze in detail this relationship using a more precise design and measurements. On the other hand, some weaker signals could have been overlooked in our current design. However, we believe that even such an exploratory study allows us to highlight important patterns and analyze them using a netnographic approach.

The study expands the current discussion on the evaluation of virtual items by showing the concrete dimensions, practices, and evaluation devices used by players. In addition, the study sheds light on several experience dimensions that have not been investigated in great detail. Confusion on rarities is an example of rule inconsistency, which frustrates players and affects asset pricing. We also reveal the connection between item bugs, which create negative experiences, and, as a result, influence developer income, and underline the importance of consistent rules in virtual item systems, showing cases of the collision between item characteristics and player's perception of item quality, and the impact of this.

In the current study, we treat the evaluation process as leaving "digital footprints" both in the Steam Community Market (resulting in price changes) and on /r/dota2 (being reflected in judgments and discussions), and show that the simultaneous study of the connection between these two footprints gives insight into the evaluation process. While discussing some results, we think about the possible mechanism, a direct causal link between the discussion and market change is not assumed nor analyzed.

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